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# Monitoring the long-term desertification process and assessing the relative roles of its drivers in Central Asia

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ABSTRACT

Desertification is one of the main ecological environmental problems in Central Asia. To prevent and eradicate this problem, it is extremely urgent to monitor the long-term desertification process and assess the relative roles of its drivers. Based on an analytical hierarchy process, in this research, the spatiotemporal features of the desertification process were surveyed from 1982 to 2012 using four indicators. Further analysis was focused on determining the relative importance of multiple driving factors causing desertification in different ecosystems. The results revealed significant desertification expansion in the western part of Central Asia, with the most severe desertification occurring in eastern Xinjiang Province and the Ustyurt Plateau, with mean desertification indexes (DIs) as high as 0.8. According to a change-year analysis, mutation years of desertification were observed from 1993 to 2002 for most vegetation types. The desertification process for different vegetation types results from different major driving factors. Climatic factors, including decreased precipitation, increased temperature and drought, were the main drivers of desertification, especially for grasslands, forests and sparse vegetation. The desertification process of sparse vegetation and croplands was expanded and triggered by human activities: oil and gas exploration in the southern Ustyurt Plateau and agricultural abandonment in northern Kazakhstan. The results also indicated that after the collapse of the Soviet Union, rangeland abandonment in eastern Kazakhstan triggered desertification reversion in grasslands. Furthermore, due to inefficient irrigation water use, severe salt accumulation in croplands of the Amu Darya River delta resulted in desertification expansion in this region. In Central Asia, the desertification process in forests and areas of sparse vegetation was extremely sensitive to climatic variations, while that in croplands and grasslands was vulnerable to human activities. Therefore, regional governments should strive to reverse desertification to protect and improve this fragile, arid ecological environment.

## 1. Introduction

Globally, the impact of desertification relates to one-fifth of the world's population, most of which lives in poverty (London and Unep, 1994), particularly in drylands. Land degradation and its manifestation in drylands, known as desertification, is still widespread (Fleskens and Stringer, 2014). Arid zones contain more than 2 billion people, most of whom have a low living standard (Johnson et al., 2006). Most areas are characterized by a low standard of living with food insecurities (Assessment, 2005), which are liable to exacerbate desertification and can place further pressure on human societies. Moreover, Central Asia has one of the world's largest arid regions, which contains five temperate deserts (Fig. 1). This arid region is in a mid-continental area with a fragile ecological environment. A large-scale agricultural transformation took place in the five states of Central Asia during the Soviet Union period. Due to the expansion of croplands and livestock numbers, the land degradation processes were substantial during the late Soviet period (Behnke and Mortimore, 2016). For example, the serious forms

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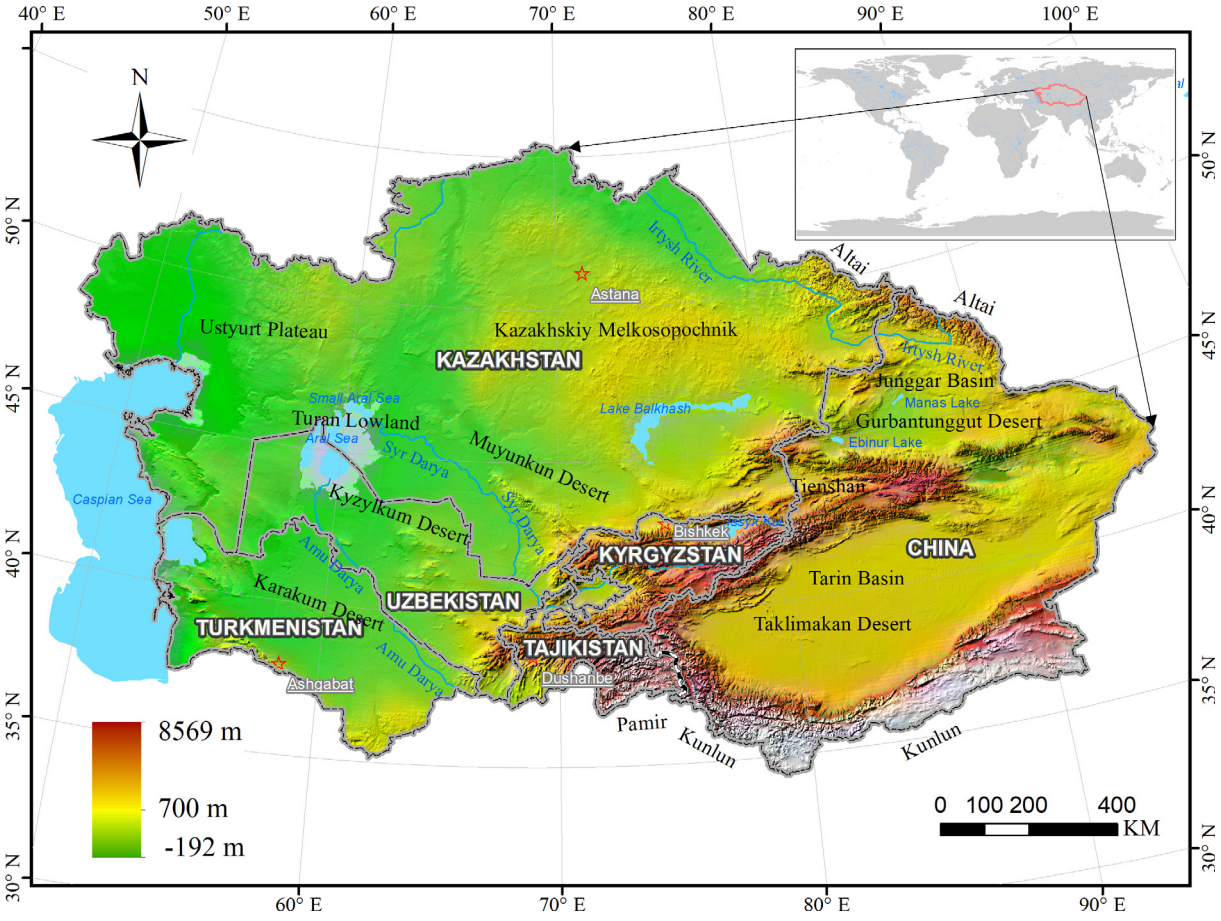


**Fig. 1.** Topographical map of Central Asia.

of degradation included the Aral Sea disaster and soil salinization (Kienzler et al., 2012). However, the degree of desertification during recent decades is still not well understood in Central Asia.

The definition of desertification enshrined by the United Nations Convention to Combat Desertification (UNCCD) indicated that desertification can be caused by climate fluctuation as well as poor land management (London and Unep, 1994). The temperature has been rising rapidly since the mid-1990s, and temperatures are currently quite high (Davi et al., 2015; Li et al., 2015b). Precipitation in the five states has displayed a slight decrease (Li et al., 2015b), whereas a slight increase has been observed in Xinjiang Province, China (Guli·Jiapaer et al., 2015). Ecosystems in Central Asia with insufficient biodiversity and stability have been subject to the desertification process under increased climate changes in recent decades (Han et al., 2016; Zhou et al., 2015b), especially in deserts (Fig. 1) (Zhang et al., 2016). Desertification is a main ecological environmental problem that results in a loss of ecosystem services and changes people's fundamental living environments, resulting in dust storms, soil erosion and reductions in vegetative cover (D'Odorico et al., 2013; Wang et al., 2017). Thus, monitoring the desertification process and assessing the relative roles of its drivers is a topic of global research interest.

Human activities are also a vital cause of the desertification process. After the Soviet Union collapsed, the socio-economic development models of the five Central Asian countries underwent different levels of changes, leading to broad-scale private ownership, large-scale human migrations, and a free market economy converted from a planned economy. As a result, the animal husbandry and agricultural management model transformed from a collective, state-owned model to a free, private market model. Indeed, the desertification process in Central Asia was bound to be influenced by diversifications of anthropogenic disturbances (Hostert et al., 2011). There are several important changes in agriculture and animal husbandry that may result in desertification moving in different directions, such as the expansion of irrigated agriculture, which results in increasing amounts of irrigation water and shrinking lakes; the abandonment of extensive croplands; the collapse of animal husbandry; and the abandonment of distant pastures (Klein et al., 2012; Xi and Sokolik, 2016). Thus, a deep understanding of the desertification process is essential to develop adaptation strategies for climate change. However, despite the social economy having undergone tremendous changes in the five Central Asian countries and Xinjiang Province, the different mechanisms driving the desertification process have received little consideration in this region.

Currently, many studies that monitor the desertification process and assess its driving factors are separate or joined on regional and global scales (Miao et al., 2015; Wang et al., 2017; Zhou et al., 2015a). Thus, it is critical to understand desertification and its response to anthropogenic disturbances and climatic variations. The lack of standardized techniques for monitoring the desertification process has led to different assessments of its spatiotemporal dimensions. One or two indexes were used in most previous studies, such as NDVI and albedo, to analyse the spatiotemporal assessment of desertification process (Kundu and Dutta, 2011; Li et al., 2016; Ma et al., 2011). Although vegetation dynamics are connected to desertification, the major characteristics of desertification are also related to soil and climate statuses, which is consistent with the strategic indicators of the UNCCD. The use of several indicators and a comprehensive assessment would be more reasonable to monitor desertification. Furthermore, the desertification process cannot be assessed during a short time period of a few years or less. Rather, desertification should be considered a land degradation process, and desertification should be evaluated over long-term periods.

According to the strategic objectives of the UNCCD, 10 years is the minimum time period for desertification assessment (Sommer et al., 2011). Accordingly, long-term-series data from 1982 to 2012 are considered in this research. The lack of agreed-upon standards for measuring the desertification process has resulted in a large divergence in research and has contributed to the sometimes critical attitudes towards the problem (Safriel, 2007). However, thus far, more efforts have been focused on desertification assessment and the responses to climate change than on the underlying drivers of human activity (Huang et al., 2015; Zeng and Yoon, 2009), especially in Central Asia. Ignoring human activity impacts on desertification may result in mistakes during the assessment of its driving factors. The desertification process of croplands and rangelands is vulnerable due to political and socio-economic instability in developing countries (Assessment, 2005). Furthermore, different vegetation types have not been considered in previous studies for assessing the desertification process or the quantitative assessment of its drivers (Li et al., 2016; Zhou et al., 2015a). Climate change and human activity have different impacts on the vegetation types in this region (Guli·Jiapaer et al., 2015; Jiang et al., 2017). Considering vegetation types is critical in the study. Therefore, knowledge of the desertification process of different vegetation types and its driving factors is necessary to develop adaptation strategies for the ecological environment, especially in the Aral Sea basin.

In this study, we monitored the long-term desertification process and quantitatively assessed the desertification drivers in Central Asia. Four indicators were selected as valid indictors for monitoring the desertification process using the analytical hierarchy process (Fensholt and Proud, 2012; Tian et al., 2015). The aims of this research were to (1) monitor the long-term desertification process and detect mutation years in the insignificant desertification processes and (2) investigate the major drivers of the desertification process. Understanding the spatiotemporal patterns of desertification dynamics will help to preserve the ecosystems in this area and maintain ecosystem services under the influences of the desertification driving factors.

## 2. Materials and methods

### 2.1. Study area

Central Asia (46°29′–96°24′E, 35°07′–55°26′N) is located deep inside the Eurasian mainland. The study area consists of five states and one province in China (Fig. 1): Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan and Xinjiang Province. This region is known as “Central Asia”; however, the definition of Central Asia is still under discussion. Following recent studies (Li et al., 2015a; Zhang et al., 2016), we delineated the areas of the five states of the CIS and Xinjiang Province in China in this study from two adjacent regions that share the same climate zone and hydrological and ecological systems (Chen et al., 2015).

The altitude gradually increases from the Caspian Sea coast and the Tarin and Junggar Basins to the Tien Shan mountain range system, Altai, and Pamir Mountains (Fig. 1) (de Beurs et al., 2015). This area has spatial variation in temperature and precipitation from the plains to the mountains. 80% of the global temperate deserts are distributed in this region, with the fragile ecological environment (Kottek et al., 2006). The main vegetation types comprise crops, grasslands, forests and sparse vegetation (Fig. 2 and Table S1, Supplementary material), which account for 14.65%, 28.61%, 1.56% and 52.18% of the total vegetation, respectively. The mountainous areas of the Tien Shan and Altai Mountains are dominated by rich grasslands and forests with vertical zonal distributions, whereas the plains regions in southern Central Asia are characterized by sparse vegetation. Some basins in Uzbekistan and Xinjiang Province, such as the Amu Darya and Manas Basins, are known for irrigated agriculture (de Beurs et al., 2015). Due to the fluctuations in climate and human activity in this region, the desertification process and its driving factors have drawn the attention of scientists.

### 2.2. Data sources

Meeting the current strategic objectives of the UNCCD and World Atlas of Desertification requires the integration of drought, vegetation degradation and soil degradation information. These organizations have described the need for improved identification and characterization of desertification regions in terms of the desertification process using various indicators (Sommer et al., 2011). Hence, many frameworks for monitoring the desertification process have been developed based on ground measurements at the local level, such as the Environmental Sensitive Area framework (Salvati et al., 2016) and the DESIRE framework (Kosmas et al., 2013). These frameworks demonstrated that changes in soil, climate and vegetation conditions were responsible for land desertification (Sommer et al., 2011). Benefitting from the availability of long-term-series datasets, we chose four key indicators of vegetation, soil and climate conditions for monitoring the desertification process: NDVI, albedo (Ma et al., 2011), the soil moisture index (SMI) (Lamchin et al., 2016; Lamchin et al., 2017) and the standardized precipitation evapotranspiration index (SPEI) (Han et al., 2015). The indicator datasets used in the paper include NDVI, albedo, gridded SMI and SPEI data (Table S2, Supplementary material).

A combination of NDVI and albedo has been widely used for desertification monitoring using the Albedo-NDVI feature space in previous studies (Becerril-Piña et al., 2016; Ma et al., 2011; Pan and Li, 2013). NDVI is a good vegetation indicator of green biomass and leaf area index for desertification study at continental or global scales (Kundu and Dutta, 2011). The NDVI dataset was acquired from the Global Inventory Monitoring and Modelling Studies (GIMMS) project, which originated from NOAA’s Advanced Very High-Resolution Radiometer (AVHRR) data (https://nex.nasa.gov/nex/projects).

Albedo reflects the absorption of solar radiation by the surface and is greatly influenced by land cover type (Coakley, 2003). Increased albedo can be an indirect indicator of the desertification process from vegetation area to bare land (Robinove et al., 1981). For example, high albedo is a feature of sandy land and salinized land. Li et al. (Li et al., 2000) reported that the aggravation of desertification was strongly related to increasing land surface albedo. The albedo dataset used in this study was derived from the Global Land Surface Satellite (GLASS) product (http://glcf.umd.edu/data/abd/), containing a high-quality, long-term data series with fine spatial resolution (Liang et al., 2013).

A reduction desertification process due to drought is one of strategic objectives of the UNCCD (Sommer et al., 2011). Agricultural drought and climate drought can be effectively monitored by SMI and SPEI, respectively. SMI is widely used to quantify the soil moisture content and represents the degree of soil moisture. In general, it can be expressed as the volume of water per unit volume of porous media ($m^3m^{-3}$) and be measured by in situ measurements and microwave observations. It can provide indirect information about land cover change. The gridded SMI dataset in this study was provided by the Soil Moisture Climate Change Initiative (CCI) project (http://www.esa-soilmoisture-cci.org/) and was generated based on six active and passive microwave spaceborne instruments (Liu et al., 2012). We obtained drought information from the global SPEI database (http://spei.csic.es/database.html). SPEI can be used to quantify the wet/dry condition at regional scale, and it has been widely used in the semi-arid and arid Central Asia (Guo et al., 2018a; Guo et al., 2018b). SPEI is defined as the difference between precipitation and potential evapotranspiration in determining drought, representing a climatic water balance (Vicente-Serrano et al., 2015). The SPEI database in this study was constructed based on the FAO-56 Penman-Monteith estimation of potential evapotranspiration.

For further analysis of different indicator datasets, the spatial resolution of different indicator datasets was used to match the medium spatial resolution of the NDVI dataset compared to the resolution of

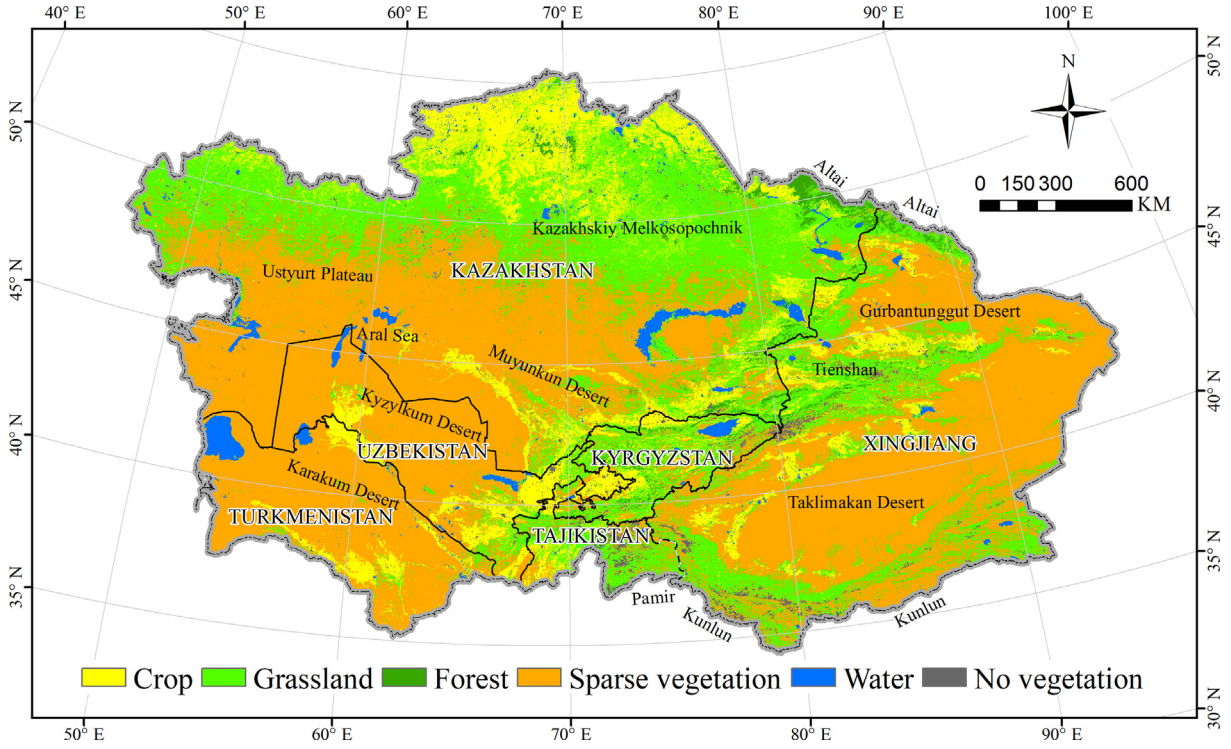


**Fig. 2.** Spatial distribution of vegetation types in Central Asia.

other datasets. All of the gridded data was resampled to 1/12° and was temporally assembled to annual values using the mean value composition.

To analyse the driving forces of desertification, the other datasets employed in this study included gridded temperature and precipitation data, vegetation-type data, gridded soil salinity data and elevation data.

We obtained monthly global gridded precipitation data during 1982–2013 at 0.5° resolution from the Global Precipitation Climatology Centre (GPCC). These precipitation data were interpolated from 67,200 stations worldwide (Schneider et al., 2017). The monthly global gridded temperature data were collected from the Global Historical Climatology Network version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS) at 0.5° resolution from 1982 to 2016, using large datasets of station data (Fan and Dool, 2008) (https://www.esrl.noaa.gov/). Based on the assessment of its drivers, the spatial resolution of the climate data was resampled to the same extent as that of the indicators.

The data for the different vegetation types (Fig. 2) was acquired from the CCI of the European Space Agency (ESA). The gridded soil salinity data was provided by the Harmonized World Soil Database of Food and Agriculture Organization to obtain the soil salinity conditions. The digital elevation data was obtained from the NASA Shuttle Radar Topographic Mission to distinguish mountains from plains (http://www2.jpl.nasa.gov/srtm/).

### 2.3. Methods

#### 2.3.1. The analytical hierarchy process

In some previous studies, desertification indexes based on comprehensive assessment have been obtained by using the geometric mean values of all indicators, each with the same weight (Bakr et al., 2012; Jafari and Bakhshandehmehr, 2016). However, significant error in the estimation of desertification expansion can result from an indicator that is less sensitive to desertification than other indicators being given the same weight. This approach does not consider expert opinion regarding regional characteristics. The analytical hierarchy process (AHP) provides a systematic approach for environmental assessment and for integrating the effects of various indicators. It has been widely used in comprehensive evaluations of desertification (Lamchin et al., 2017; Nandy et al., 2015; Sadeghravesh et al., 2015; Wang et al., 2015). The AHP method has some advantages over other, multi-criteria methods in some conditions, such as its flexibility and intuitive appeal to experts and the ability to evaluate the consistency of the judgements (Ramanathan, 2001). Desertification study involves multiple research areas; thus, AHP it is a suitable technique as it considers the opinions of experts in different fields. Additionally, AHP in desertification assessment can reveal the relative importance values of different indicators contributing to desertification. The weights obtained by AHP are consistent with region-specific environmental characteristics (Budak et al., 2018).

The weight of each variable was determined from the pairwise comparison matrices of the AHP (Saaty, 1977). In the pairwise comparison matrix, if the indicator of desertification is more dominant than another indicator, this element in the matrix can be filled between 2 and 7 based on the degree of importance. Otherwise, the value changes between 1/2 and 1/7 (Table 1). The pairwise comparison matrix (Table 2) was completed by 15 experts engaging in desertification studies from our institute according to the relative importance of the

**Table 1**
The relative importance between different indicators.

| 1/7 | 1/6 | 1/5 | 1/4 | 1/3 | 1/2 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Extremely Less important | | Strongly | | Moderately | | Equally | Moderately More important | | Strongly | | Extremely | |

**Table 2**
A pairwise comparison matrix for desertification.

| Indicator | NDVI | Albedo | SMI | SPEI | Weight |
|---|---|---|---|---|---|
| NDVI | 1 | 2(7/15) | 4(6/15) | 5(8/15) | 0.5065 |
| Albedo | 1/2 | 1 | 2(6/15) | 3(9/15) | 0.2651 |
| SMI | 1/4 | 1/2 | 1 | 2(10/15) | 0.1424 |
| SPEI | 1/5 | 1/3 | 1/2 | 1 | 0.0861 |
| Consistency ratio (CR): 0.0079 | | | | | |

two criteria (Table 1). We selected the highest frequency value of each element in the comparison matrix. The pairwise comparison matrix can be assessed using the consistency of the judgements. Consistent with the results of previous studies, the weighted results indicated that NDVI and albedo are the major indicators of the desertification process in the study area. Most previous studies used these two indicators, either separately or jointly, to analyse the spatial and temporal patterns of desertification (Kundu and Dutta, 2011; Li et al., 2016; Ma et al., 2011).

In AHP, the consistency ratio (CR) was calculated to reveal whether the judgements of the pairwise comparison matrix were randomly filled. When the CR is lower than 0.01, the matrix is reasonable; otherwise, we should change the values of the pairwise comparison matrix and recalculate the weight. In this research, the value of CR is 0.0079 (Table 1) and acceptable.

$$CR = \frac{CI}{RI} \tag{1}$$

where RI is the average of the resulting consistency index and was obtained from the order matrix provided by Saaty (Saaty, 1977). CI was computed using Eq. (2):

$$CI = \frac{m_{\max} - n}{n - 1} \tag{2}$$

where $m_{max}$ and n are the principal eigenvalue and size of the pairwise comparison matrix, respectively.

In the final step, standardization of the indicator values is necessary before compressive evaluation of desertification. This step can remove the different amplitudes and units among the indicators. The standardization processes are calculated using Eqs. (3) and (4):

For a favourable indicator,

$$Y_{ik} = \frac{\max X_{ik} - X_{ik}}{\max X_{ik} - \min X_{ik}} \tag{3}$$

For an unfavourable indicator,

$$Y_{ik} = \frac{X_{ik} - \min X_{ik}}{\max X_{ik} - \min X_{ik}} \tag{4}$$

where $Y_{ik}$ is the standardization value of $X_{ik}$, which is the value of the ith indicator in the kth year.

The desertification index (DI) based on the combined indicators is acquired using the method of weighted linear combinations (Wang et al., 2008).

$$DI = \sum_{i=1}^{n} W_i \times Y_i \tag{5}$$

where DI is the desertification index. $W_i$ is the weight of the ith indicator, and $Y_i$ is the standardization value of the ith indicator.

DI as a new indicator of desertification process was established in the study. Although the indicator of desertification process is difficult to verify, two indirect validations of desertification dynamics were carried out in the study. First, the desertification can be indirectly monitored based on the NPP change trend proposed by the Atlas initiative and UNCCD (Cherlet et al., 2018; Sommer et al., 2011). The areas with decreased NPPs experience desertification expansion; that is, a negative relationship between DI and NPP should exist for the time period. Therefore, a quantitative analysis of the relation between change trend in these two indexes could be conducted for the validation of desertification process. NPP data was derived from MOD17A3. Due to MOD17A3 data availability, the time period from 2000 to 2012 was chosen in the relationship analysis. Second, land conversions between grasslands and sparse vegetation are a result of desertification process. When grassland has been degraded into sparse vegetation or sparse vegetation has been improved into grasslands, land experienced desertification expansion or desertification reversion, respectively, indicating a correct desertification dynamic in this region. Land use data was acquired from the European Space Agency. Because of data availability, the time period from 1992 to 2012 was chosen in the second validation.

### 2.3.2. Linear regression analysis

The linear regression analysis method was applied to measure the desertification dynamics and climatic variations in this study. The long-term series values were computed to acquire the slope coefficients of each pixel. Combining the results of the Mann–Kendall significance test, we can analyse the significance of trends in the long-term series values. The slope of the trend of each pixel was calculated as follows (Chatfield, 2016):

$$Slope = \frac{n\sum_{n}^{i=1} i \times X_i - \sum_{n}^{i=1} i \times \sum_{n}^{i=1} X_i}{n\sum_{n}^{i=1} i^2 - (\sum_{n}^{i=1} i)^2} \tag{6}$$

where $i$ and n are the number of years and year range from the year 1982 to 2012, respectively, during the study period; and $X_i$ represents the DI value in the ith year.

Based on the Pearson correlation, the correlation coefficients between the annual DI, annual temperature and annual precipitation were computed. When the correlation coefficients were significant at the 95% confidence level, it indicates that DI and climate change have a closer relationship.

### 2.3.3. Buishand range test

Studies including the Buishand range test, proposed by Buishand in 1982 (Buishand, 1982), originally addressed the homogeneity of rainfall records over long periods of time (Buishand, 1982). At present, the Buishand range test is recognized as a useful statistical method for change-point detection (Alexandersson and Moberg, 2015).

Let X denote a normal random variate; then, the change-point can be proposed using the following model:

$$x_i = \begin{cases} \mu + \varepsilon_i & i = 1, 2, \cdots, m \\ \mu + \Delta + \varepsilon_i & i = m+1, \cdots, n \end{cases} \tag{7}$$

$\varepsilon \approx N(0, \sigma)$. The null hypothesis is $\Delta = 0$ and the alternative hypothesis is $\Delta \neq 0$.

The rescaled adjusted partial sum ($S_y^*$) is computed using the following formula (Buishand, 1982):

$$S_k^* = \sum_{i=1}^{k} (x_i - \hat{x}) \quad i = 1, 2, \cdots, n \tag{8}$$

When $S_k^*$ rises and then falls to around zero, the time series is homogeneous. When $S_k^*$ has reached a minimum or maximum, the year y has a mutation point. The test statistic (R) is calculated as follows:

$$R = \frac{(\max\limits_{0 \le k \le n} S_k^* - \min\limits_{0 \le k \le n} S_k^*)}{\delta} \tag{9}$$

### 2.3.4. Residual analysis

The relative importance of human activities and climate change in desertification dynamics was quantitatively determined using the residual analysis method (Evans and Geerken, 2004). The DI values were calculated using the four indicators as per the Eq. (5). The annual DI was at 1/12° resolution from 1982 to 2012. Then, the predicted DI

values were calculated using the regression model between the annual DI and annual mean temperature and annual accumulative precipitation (Wessels et al., 2012). The regression model is expressed as the Eq. (10). The regression coefficients of precipitation and temperature were determined based on the ordinary least squares procedure (Ji and Peters, 2004). The DI residuals were obtained by calculating the differences between the DI values and the predicted DI values of each pixel using Eq. (11). The significance test of the DI residuals can be divided into two behaviours. First, the areas with the insignificant change trend of the DI residuals showed that the desertification process could be explained by climate change. Second, the areas with the significant change trend of the DI residuals indicated that the desertification process was not explained by climate change but rather by anthropogenic disturbances. The DI residuals were measured as follows:

$$predicted\ \ DI = \ \beta_0 + \beta_1 \times \Pr e + \beta_2 \times Tem + \varepsilon \quad (10)$$

$$DI\ \ residuals = \ \ DI - predicted\ \ DI \quad (11)$$

where Pre and Tem are annual accumulative precipitation and annual mean temperature of each pixel, respectively; $\beta_1$ and $\beta_2$ represent regression coefficients of precipitation and temperature, respectively; $\beta_0$ is the intercept of the regression model; and $\varepsilon$ represents random error.

## 3. Results

### 3.1. The desertification dynamics from 1982 to 2012

Before analysing the desertification process, a long-term series of the DI of each pixel was used to distinguish areas of no vegetation, including aeolian dunes, water bodies, and areas of permanent snow and ice, in the study area. The desertification process in this study was monitored according to changes in vegetation and soil status. The indicators (NDVI, albedo and SMI) were not suitable for monitoring the desertification process in water bodies and areas of permanent snow and ice. Regions of aeolian dunes have already degraded into the no-vegetation mobile desert zone. For example, a previous study showed that sand dunes prevailed in the Taklimakan Desert at least 5.3 Ma ago (Sun and Liu, 2006). The desert zone has been in a stable state in the absence of human activity. In this study, the desertification process refers to the disturbance or destruction of the original land state, which creates imbalance. In the no-vegetation mobile desert zone, the essential characteristics of the desert have not changed over the years, having no fertility or vegetation. No desertification process can be observed in this region. Therefore, the study focused on the desertification process in the vegetated areas and applied additional masks. We excluded areas of disturbance from no-vegetation regions. Combined with Google Earth software to explore aeolian dunes in the Taklimakan Desert, we chose some samples and determined the extract threshold of the sand sheets based on the DI from 1982 to 2012. When 95% of the DI values exceeded 0.76 in the pixel, this pixel was identified as no-vegetation or aeolian dunes. The spatial distributions of no-vegetation areas are shown in Fig. 3. The results showed that most of the no vegetation areas are scattered in the Taklimakan Desert and eastern Xinjiang Province. Therefore, we needed to mask these regions in the subsequent desertification process analysis.

The spatial distribution of the mean DI from 1982 to 2012 (Fig. 4a) displayed high values in the Karakum, Kyzylkum and Gurbantunggut Deserts, with mean DIs as high as 0.8. Low values of the mean DI were detected in eastern Kazakhstan and the Altai and Tien Shan Mountains, with mean DIs as low as 0.25, which confirms our understanding that the DI values in the mountains are lower than those in the deserts. Fig. 4b shows the annual desertification process. Most of the upward trend areas were observed in the western part of Central Asia and eastern Xinjiang Province, whereas most of the significant downward areas occurred in eastern Central Asia, especially in Kazakhskiy Melkosopochnik and Tien Shan Mountain. Western Kazakhstan and eastern Xinjiang Province have undergone significant desertification expansion, and thus, the desertification process in this region has a regional feature.

The validation of desertification dynamics is crucial in Central Asia. According to the relationship between DI change and NPP change, a definite negative correlation was identified during the time period from 2000 to 2012, with a high $R^2$ amounting to 0.523 (Fig. S1, Supplementary material). Concerning the validation of the relationship between land use changes and DI change, 500 verification points were randomly selected in the study, including 200 points changed from grassland to sparse vegetation and 300 points changed from sparse vegetation to grasslands. The result indicated that the accuracy of desertification dynamics is up to 82.84% (Fig. S2, Supplementary material). Thus, the indicator established in the study is reliable for monitoring desertification dynamics.

After the results of the change trend in DI and the Mann–Kendall test are combined, the desertification process can be effectively divided into five classes (Table 3). Fig. 4c reveals that the desertification degrees in Central Asia were not uniform in space over the last 30 years and that the ecological environment was improving; however, the desertification expansion in some regions cannot be ignored. Most of the vegetated areas (43.87%) underwent slight or significant desertification reversions, whereas some areas underwent light or significant desertification expansion (33.39%); 22.74% of vegetated areas were determined to be stable areas. Moreover, desertification expansion in western Kazakhstan and eastern Xinjiang Province was more serious than that in other regions.

Regarding the statistical results of the percent changes in DI, the desertification process for different vegetation types varied between the five Central Asian countries and Xinjiang Province of China. In the five Central Asian countries, higher percentages of desertification expansion were found for crops than for the other vegetation types (Fig. 4d), where 13.12% and 26.76% of pixels of crops showed significant and slight desertification expansion, respectively, followed by those of sparse vegetation. For grasslands and forests, the proportions of desertification expansion areas were almost the same and were less than those for crops and sparse vegetation, with 26.34% and 27.55% of the pixels, respectively. Moreover, the proportions of desertification reversion of grasslands and forests were 54.47% and 51.91%, respectively, greater than those of crops and sparse vegetation.

Compared with the desertification process of the five Central Asian countries, in Xinjiang Province, sparse vegetation and grasslands had higher proportions of desertification expansion than grasslands and forests (Fig. 4d). Sparse vegetation and grasslands accounted for 48.90% and 29.82% with desertification expansion, respectively. In contrast, more proportions of desertification reversion were identified for crops and forests. Crops accounted for 30.13% and 29.63% of the pixels with slight and significant desertification reversion, respectively, whereas forests accounted for 32.95% and 27.20% of the pixels that showed slight and significant desertification reversion, respectively. Overall, the differences in the desertification process for different vegetation types and different regions are obvious.

### 3.2. Change-year detection in the desertification process from 1982 to 2012

The annual variation in average DI over different regions and different vegetation types from 1982 to 2012 is shown in Fig. 5. In the five Central Asian countries, DI exhibited a slight decreasing trend for crops and sparse vegetation during the first 10 years. However, in the last ten years, the increase was rapid for crops, grasslands and sparse vegetation ($P < 0.01$). The desertification process of most vegetation types gradually changed from desertification reversion to desertification expansion.

In contrast, the variations in annual DI in Xinjiang Province were less significant for most vegetation types than for the five Central Asian countries, especially for crops and grasslands. A significant increasing

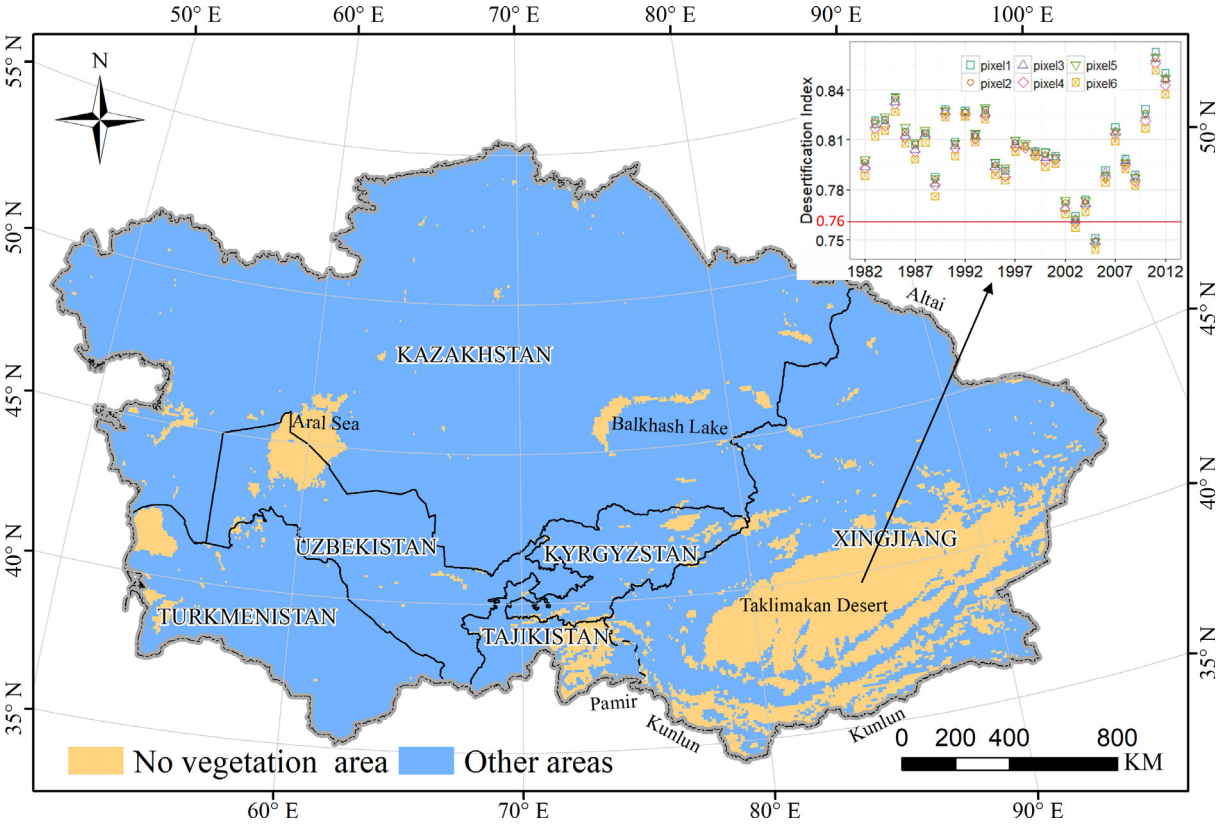


**Fig. 3.** Spatial distribution of no-vegetation regions in Central Asia.

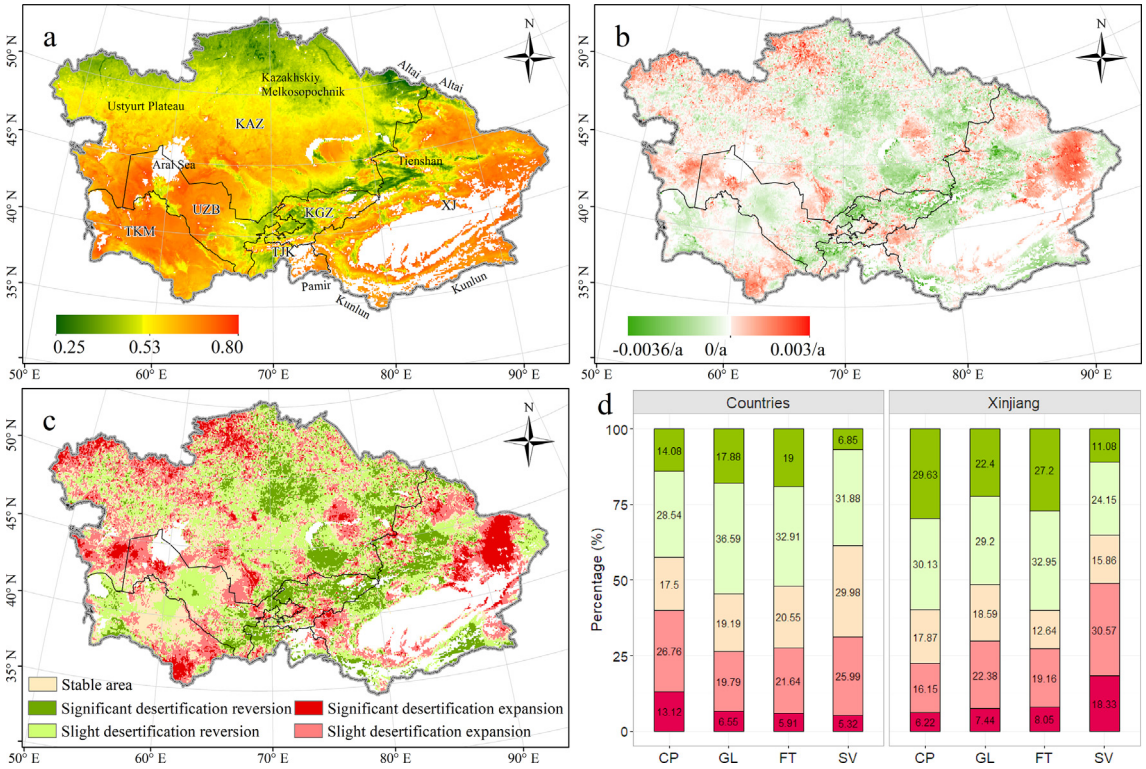


**Fig. 4.** Spatial distribution and change trends in the mean desertification index (DI) from 1982 to 2012. (a) Spatial distribution of the mean DI; (b) annual change trends in DI; (c) the change trends classified into five classes of significant desertification reversion, slight desertification reversion, stable area, slight desertification expansion, and significant desertification expansion; and (d) the percent changes in DI for different regions and different vegetation types. Countries: the five Central Asian countries; Xinjiang: Xinjiang Province of China; CP: crop; GL: grassland; FT: forest; SV: sparse vegetation; KAZ: Kazakhstan; UZB: Uzbekistan; KGZ: Kyrgyzstan; TJK: Tajikistan; TKM: Turkmenistan; XJ: Xinjiang Province. The legend for (d) is the same as that for (c).

**Table 3**
Division of desertification degree.

| $S_{DI}$ | Z | Desertification classification |
|---|---|---|
| ≥0.001 | ≥1.96 | Significant desertification expansion |
| 0.0002–0.001 | −1.96–1.96 | Slight desertification expansion |
| −0.0002–0.0002 | −1.96–1.96 | Stable area |
| −0.001–−0.0002 | −1.96–1.96 | Slight desertification reversion |
| < −0.001 | ≤−1.96 | Significant desertification reversion |

trend was observed during the first 10 years for forests and during the last 10 years for sparse vegetation. The desertification process of grasslands and forests gradually changed from desertification expansion to desertification reversion, whereas the desertification process of crops gradually changed from desertification reversion to desertification expansion. However, sparse vegetation was under consistent desertification expansion during the study period.

In general, the desertification process in the five Central Asian countries gradually changed from desertification reversion to desertification expansion. However, in Xinjiang Province, the desertification process was not consistent among the different vegetation types. It was noticed that the desertification process of sparse vegetation was under consistent expansion.

Based on the results of the Mann–Kendall test, the desertification process can be classified as involving significant changes ($Z \leq -1.96$ or $Z \geq 1.96$) or insignificant changes ($-1.96 < Z < 1.96$). We found that the vegetated regions with significant or stable changes were relatively concentrated in eastern Xinjiang Province. For areas with an insignificant desertification process, we detected the mutation years using the Buishand range test (Buishand, 1982). The mutation years detection was divided into three intervals (Fig. 6a). This classification indicated that most regions with mutation years from 1993 to 2002 were observed in the eastern part of Kazakhstan, whereas most areas with mutation years from 2003 to 2012 were distributed in western Central Asia. We also found that most of the vegetated regions in the central part of Central Asia had mutation years from 1982 to 1992 during the study period.

Mutation years for different vegetation types and different regions were compared as shown in Fig. 6b. The proportions of vegetation-type mutation years for different time intervals varied between the five Central Asian countries and Xinjiang Province. In the five Central Asian countries, crops (39.49%), grasslands (45.84%) and forests (47.83%) had the highest percentages of mutation years in the second ten-year period. In contrast, a higher proportion of mutation years in the last ten-year period was found for sparse vegetation, followed by the second ten-year period. In Xinjiang Province, a higher proportion of mutation years in the second ten-year period was observed in all vegetation types, including more than 50% of the pixels for grasslands, forests and sparse vegetation. Grasslands (31.62%), forests (25.74%) and spare vegetation (34.83%) had higher proportions of mutation years in the last ten-year period than in the first ten-year period. For different vegetation types, the difference in natural vegetation between different mutation years is greater than that in artificial vegetation. Some drivers of desertification for different vegetation types and different regions may be transformed, leading to desertification in different processes, especially after 1992.

### 3.3. Assessment of the relative roles of climatic variations and anthropogenic disturbances

Central Asia has experienced serious climatic variations in recent decades. Precipitation has presented different spatial trends, with increasing trends found in Xinjiang Province and Kazakhskiy Melkosopochnik (Fig. 7a). Temperatures in most regions showed a clear upward trend, with the high change rate up to 0.09 °C/a in eastern Xinjiang Province (Fig. 7b). These findings confirmed the findings from previous studies that Xinjiang Province has become warm and humid (Guli·Jiapaer et al., 2015; Shi et al., 2007) and that the five Central Asian countries have become warm and dry (de Beurs et al., 2015; Lioubimtseva, 2014). Different patterns of climate change among the five Central Asian countries and Xinjiang Province have inevitably had different impacts on the desertification process.

In most of Central Asia, a negative correlation was found between DI and precipitation, and a positive correlation was observed between DI and temperature (Fig. 7c and 7d). DI showed higher correlations with precipitation than with temperature, especially in the northern part of Kazakhstan and the Ustyurt Plateau, which confirms that precipitation is the major driver of the expansion and reversion of desertification on Earth (D'Odorico et al., 2013). Moreover, because the desertification process is driven by several factors, the relative importance of climatic variations and anthropogenic disturbances were detected for the desertification process, as shown in Fig. 7e and f. The results demonstrate that most areas with light-orange and light-green shading showing insignificant changes in DI residuals can be explained

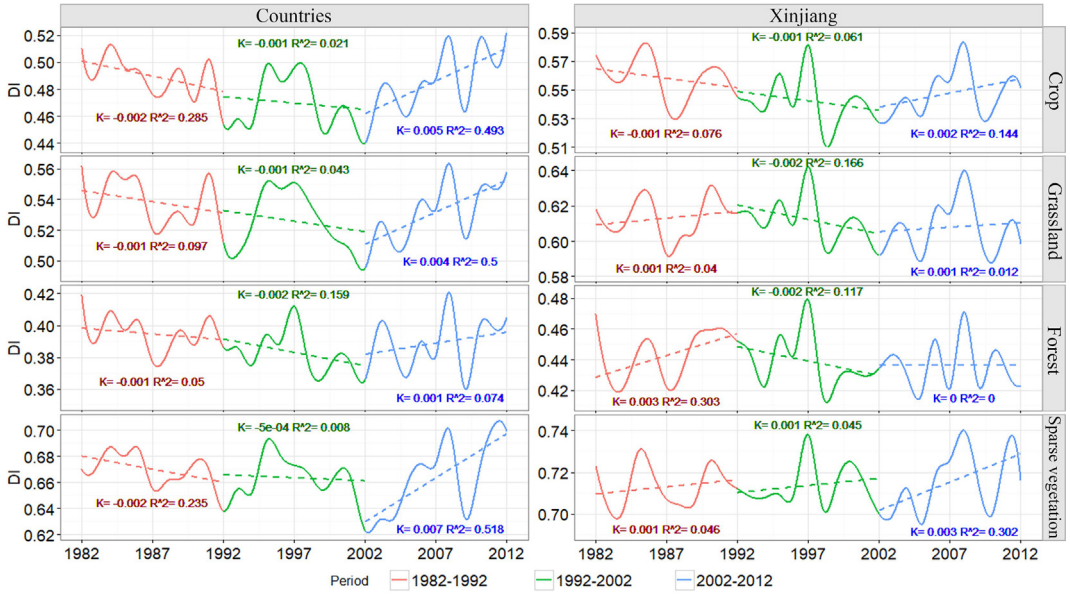


**Fig. 5.** Dynamics of the annual DI for different regions and vegetation types. Countries: the five Central Asian countries; Xinjiang: Xinjiang Province of China.

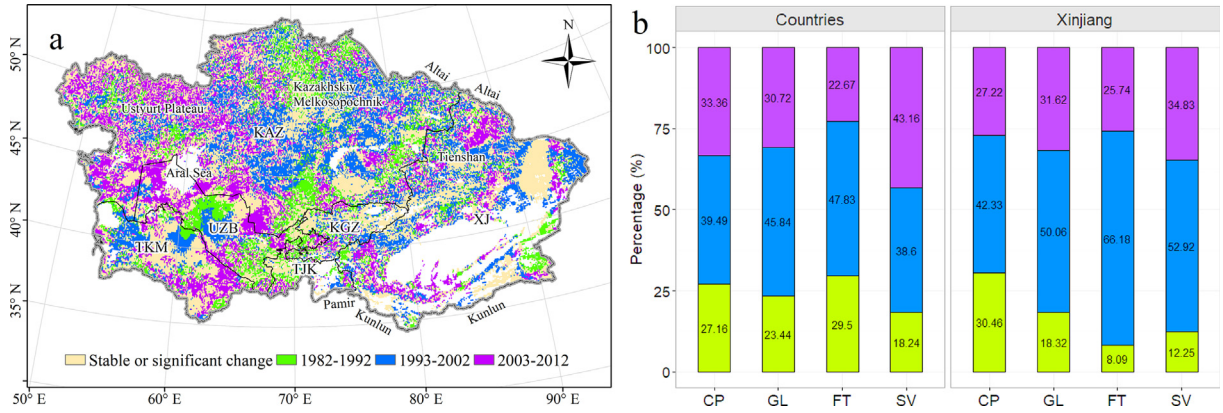


**Fig. 6.** Spatial distribution of mutation years classified into three periods (a) and statistical results of mutation years for different regions and different vegetation types (b). Countries: the five Central Asian countries; Xinjiang: Xinjiang Province of China; CP: crop; GL: grassland; FT: forest; SV: sparse vegetation. KAZ: Kazakhstan; UZB: Uzbekistan; KGZ: Kyrgyzstan; TJK: Tajikistan; TKM: Turkmenistan; XJ: Xinjiang Province. The legend for (b) is the same as that for (a).

by climate change. Desertification reversion of grasslands and forests was found in the south part of Kazakhstan and the Tien Shan and Altai Mountains, and desertification expansion of sparse vegetation was identified in the Gurbantunggut Desert, the margins of the Taklimakan Desert, eastern Xinjiang Province and the southern part of Turkmenistan. Thus, climatic factors were the main drivers of the desertification process for natural vegetation in Central Asia.

Other than climatic drivers of desertification, we also considered some human activity drivers, which could affect the desertification process. According to the residual analysis (Fig. 7f), desertification was reversed in eastern Kazakhstan, Kyrgyzstan, Tajikistan and northern Xinjiang Province, and desertification was expanded in the southern northern Kazakhstan, Ustyurt Plateau and the central region of eastern Xinjiang Province. These changes were not explained by climatic fluctuations, with significant change observed in the DI residuals, and thus were mainly caused by anthropogenic disturbances.

## 4. Discussion

### 4.1. Major drivers of the desertification process for grassland and forest

Desertification is a consequence of a combination of multiple driving factors (D'Odorico et al., 2013). Thus, we discuss the major drivers of the desertification process for different vegetation types.

For the grasslands and forests in the Tien Shan and Altai Mountains and southern Kazakhstan, increased precipitation is the major driving factor causing desertification reversion. These vegetation types are widely distributed in these regions, and strong negative correlations between grassland and forest DI and precipitation exist in the five Central Asian countries and Xinjiang Province (Fig. 7c); e.g., the desertification reversion of grasslands with increased precipitation was pronounced in southern Kazakhstan. Moreover, an increase in grasslands has occurred due to the transformation of sparse vegetation, and the boundary of the grassland ecosystem has expanded to the Muyun Kum Desert (Chen et al., 2015). In the mountains, although increased precipitation can trigger water erosion, the precipitation can be conducive to plant growth, which led to desertification reversion (Zhao et al., 2011). This finding is consistent with a previous finding that a higher proportion of desertification reversion was found in grasslands and forests according to a desertification dynamics analysis (Fig. 4). In addition, DI residuals in the Altai Mountains exhibited an insignificant change for grasslands during the study period (Fig. 9). In contrast, decreased precipitation was observed in the western part of Central Asia, and more regions experienced desertification expansion, especially in the grasslands of the Ustyurt Plateau.

For grasslands in eastern Kazakhstan, Tajikistan and Kyrgyzstan, pasture abandonment is a major driving factor affecting desertification reversion. In the Soviet era, livestock was heavily funded by the government, and the increase in livestock inventories exceeds the carrying capacity of the pastures, which led to overgrazing and the strong desertification expansion of rangelands (Behnke and Mortimore, 2016; Hostert et al., 2011). However, after the disintegration of the Soviet Union, this subsidy for livestock disappeared following the national political independence (Karnieli et al., 2008), and livestock profits were greatly reduced. As Kazakhstan, Kyrgyzstan and Tajikistan largely withdrew from livestock production, decreases in livestock inventories of 60.57%, 42.12% and 27.65% were recorded from 1991 to 2002, respectively (Fig. 8a). Alimaev and Jr (2008) showed that overgrazing was mitigated because of the abandonment of remote and summer pastures. In addition, Huang et al. (Huang et al., 2018) reported that the decrease in human appropriation of net primary production (HANPP) in rangelands was triggered by the negative effect on livestock production after the Soviet Union collapsed. As pasture recovery progressed, the desertification of grasslands reversed. Robinson (Robinson, 2016) reported decreased livestock inventories as a main force explaining the desertification reversion of grasslands in these areas. This result is consistent with the change-year detection result of the present study that most grasslands in these regions had mutation years in the desertification process from 1992 to 2002 (Fig. 6). This phenomenon is also evident in DI residuals in eastern Kazakhstan (Fig. 9). The desertification process of grasslands gradually changed from desertification expansion before 1991 to desertification reversion after 1991. By contrast, in Turkmenistan, Uzbekistan and Xinjiang Province, the livestock inventories from 1990 to 2006 increased by 35%, 190.89% and 54.95%, respectively (Fig. 8a). To prevent a collapse in livestock inventories after the 1990 s, the governments of Uzbekistan and Turkmenistan continued to promote livestock production (Robinson, 2016), resulting in increased livestock inventories and exacerbation of the desertification process of rangelands in these countries. In Xinjiang Province, livestock inventories were increased due to strong government support. Livestock grazing has expanded from plains areas to fragile mountain regions, increasing the desertification of grasslands in the western Tien Shan Mountains of Xinjiang Province (Wu et al., 2010). As shown in Fig. 9, a significant increasing trend in annual DI residuals was observed for grasslands in this region.

### 4.2. Major drivers of the desertification process for croplands

The desertification of crops varied between the five Central Asian countries and Xinjiang Province. After the Soviet Union collapsed in 1991, socio-economic development models underwent different levels of change in the five Central Asian countries. The annual variability in

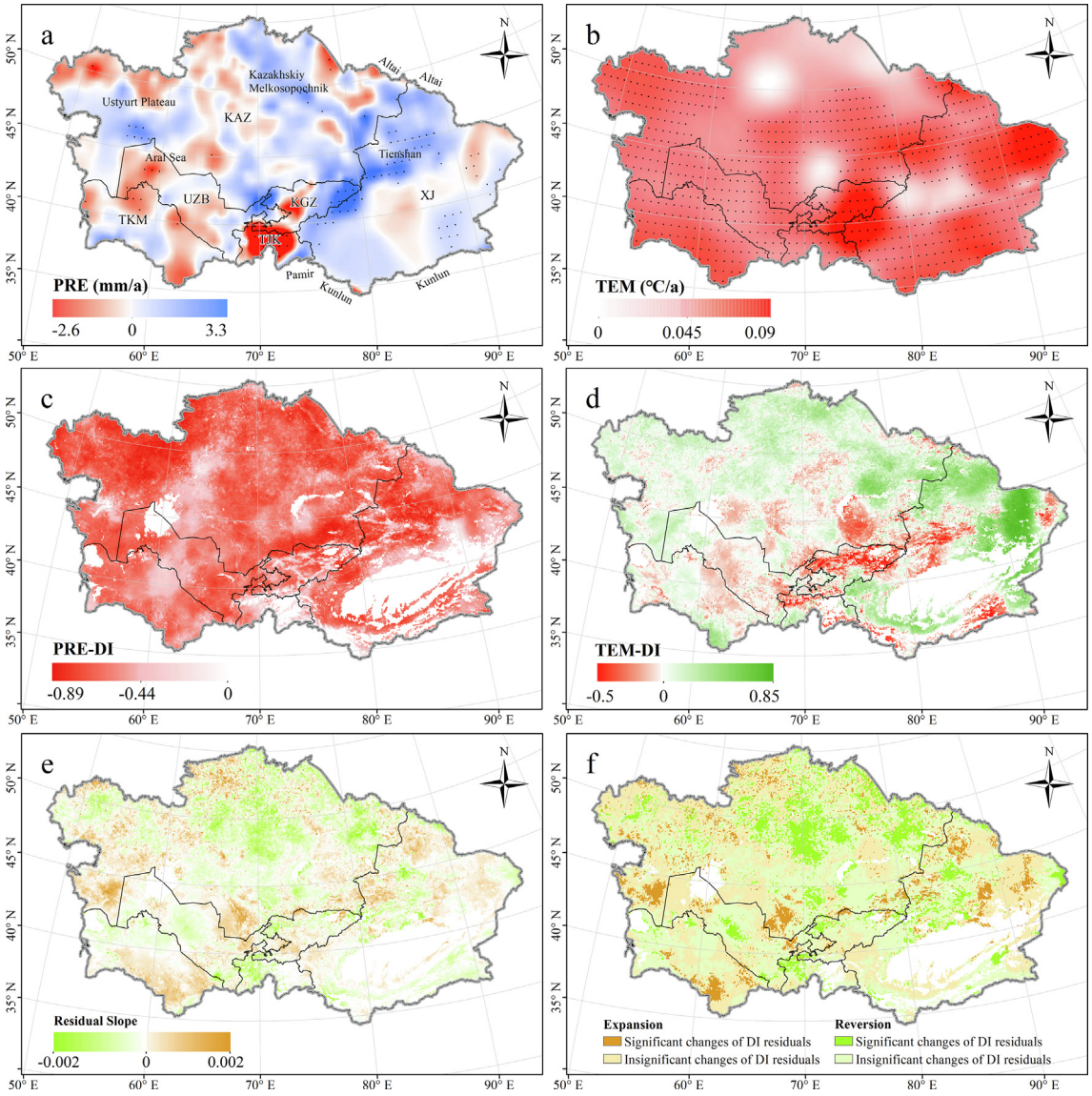


**Fig. 7.** Overall climatic factor trends and the DI regression residuals with climatic factors. (a) and (b) show the annual change trends in precipitation and temperature. The black spots show the significant change trends in the climatic factors. (c) and (d) show the correlation coefficients between DI, precipitation and temperature. (e) and (f) show the overall trends of the DI regression residuals and overlay results of the change trends in DI and significant changes (p-value) in the DI residuals. Light-green and light-orange shading shows an insignificant change trend of the DI residuals, and the desertification process could be explained by climate change. The dark-green and dark-orange shading shows a significant change trend of the DI residuals, and the desertification process was not explained by climate change but rather by anthropogenic disturbances (f). KAZ: Kazakhstan; UZB: Uzbekistan; KGZ: Kyrgyzstan; TJK: Tajikistan; TKM: Turkmenistan; XJ: Xinjiang Province.

cropland area in Kazakhstan was significant (Fig. 8b). Millions of hectares of croplands were abandoned as a result of insecure land tenure and reduced agricultural subsidies in Kazakhstan (Zhou et al., 2015b) (Fig. 8b), particularly in northern Kazakhstan (Fig. 7f). Almost 8 million hectares of abandoned croplands in Kazakhstan, as shown in Fig. 8b, occurred after 1991. However, croplands in northern Kazakhstan have undergone severe soil erosion and soil fertility depletion. Although the soil might have recovered some carbon after agricultural abandonment (Fargione et al., 2008), losses of soil organic matter as high as 40% are estimated for croplands of Kazakhstan due to poor management (Mirzabaev et al., 2016). In this arid region, vegetation was slow to recover, and many farmlands became sparse vegetation, leading to the exposure of surface soil. This exposed soil aggravated the desertification expansion under strong wind erosion in Kazakhstan (Mirzabaev et al., 2016). These observations explain the higher proportion of desertification expansion of crops in Kazakhstan than in Xinjiang Province (Fig. 4d). The significant increasing trend in DI residuals was stronger after 1991 than before 1991 (Fig. 9), resulting in some pixels of the mutation years being observed on the northern edge of Kazakhstan during 1993 to 2002 (Fig. 6a). In contrast, large areas of sparse vegetation were converted into croplands in northern Xinjiang Province (Fig. 8b) (Feng et al., 2012). The area of croplands in Xinjiang Province has increased from 3.13 to 3.95 million hectares, resulting in a significant change in DI residuals in this area (Fig. 9) and some pixels of the mutation years from 2003 to 2012, especially in the northern part (Fig. 6a). However, with the increase in cultivated land, the increased exploitation of irrigation water resources has caused the dramatic drop in river inflow, leading to the shrinking of Manas Lake and Ebinur Lake (Cheng et al., 2006; Yao et al., 2014). Due to the consistent recession, desertification expanded around these lakes.

The spatial distributions of soil salinity provided by the Food and Agriculture Organization of the United Nations revealed that croplands

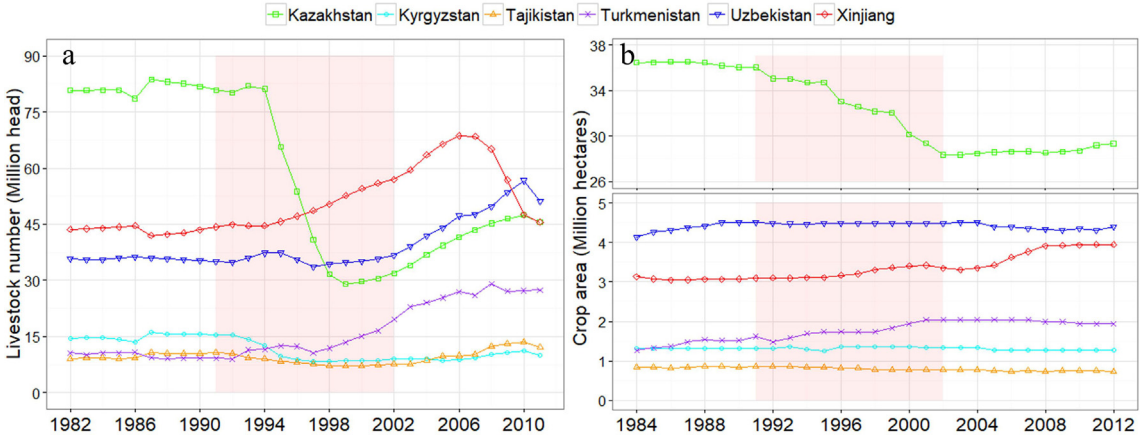


**Fig. 8.** Annual changes in livestock inventories (a) and cropland area (b) in different regions of Central Asia. The red shadows stress the variations that appeared after the disintegration of the Soviet Union. The data on livestock inventories (measured in terms of sheep units) and crop areas were derived from the FAO and World Bank Open Data (http://data.worldbank.org/), respectively.

in the Aral Sea basin were spatially aggregated, with severe soil salinization under desertification expansion (Fig. 10a and b), especially in the Amu Darya River delta, which has a shallow groundwater table. Because the salts dissolved in groundwater are filtered into the rooting zone through filtration by capillary action, the removal of salts from groundwater by vegetation can increase soil salinity in this region (D'Odorico et al., 2013; Khamzina et al., 2008). Additionally, owing to excessive or inefficient irrigation water use, secondary soil salinization was found in arable lands of the Aral Sea basin (Ibrakhimov et al., 2007; Kitamura et al., 2006). The overall irrigation efficiency was extremely low, and approximately 62% of the irrigation water withdrawn was wasted before it was available for crop production (Kitamura et al., 2006). This wasting of water increased the groundwater table during the cropping season, which exacerbated the soil salinization through strong evapotranspiration of the groundwater. Because of excessive or inefficient irrigation water use, severe salt accumulation occurred in the croplands of the Amu Darya River delta, resulting in a significant change in DI residuals in this region (Fig. 9) (Forkutsa et al., 2009).

### 4.3. Major drivers of the desertification process for sparse vegetation

The proportion of sparse vegetation was approximately 52.18% of the vegetated areas. The desertification process of sparse vegetation in different regions resulted from different main driving factors. In Xinjiang Province, increased temperature may be the major driver affecting desertification expansion for sparse vegetation in the Gurbantunggut Desert and the margins of the Taklimakan Desert. Desertification process in these areas, with scattered sparse vegetation, was mainly controlled by climate change, especially changes in precipitation and temperature (Wang et al., 2009). Although precipitation increased slightly in these areas, desertification continued to expand, which shows that increased precipitation is not the only factor that controls desertification (Wang et al., 2009). Moreover, the DI values of sparse vegetation presented stronger positive relationships with temperature in these regions than in other regions (Fig. 7d). Therefore, increased temperature may inhibit the growth of sparse vegetation, resulting in consistent desertification expansion during the study period (Fig. 5). However, in the middle stream of the Tarim River, desertification expansion of sparse vegetation was mainly caused by human activities (Fig. 7f). Introduction of the water transport dike in the middle stream led to a decline in vegetation coverage on both sides of the river (Guo et al., 2017).

In addition to increased temperatures, drought is also a major driver affecting the desertification expansion of sparse vegetation because of increased temperatures and decreased precipitation in eastern Xinjiang Province and the southern part of Turkmenistan. Sparse vegetation in these areas has undergone desertification expansion because of decreasing precipitation. The DI values of sparse vegetation presented higher negative correlations with precipitation in these areas (Fig. 7c). This result is mainly because sparse vegetation growth relies on precipitation. Furthermore, rising temperatures generally increase surface evaporation and limit sparse vegetation growth (Jiang et al., 2017). Annual DI in these areas revealed positive relationships with temperature (Fig. 7d) and exhibited a significant change in DI residuals for

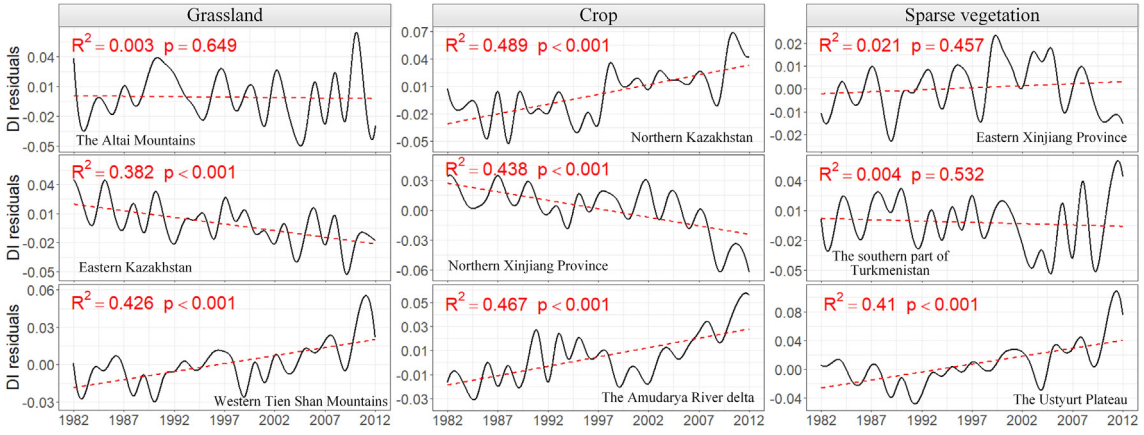
Grassland
Crop
Sparse vegetation
DI residuals
R² = 0.003 p = 0.649
The Altai Mountains
R² = 0.489 p < 0.001
Northern Kazakhstan
R² = 0.021 p = 0.457
Eastern Xinjiang Province
R² = 0.382 p < 0.001
Eastern Kazakhstan
R² = 0.438 p < 0.001
Northern Xinjiang Province
R² = 0.004 p = 0.532
The southern part of Turkmenistan
R² = 0.426 p < 0.001
Western Tien Shan Mountains
R² = 0.467 p < 0.001
The Amudarya River delta
R² = 0.41 p < 0.001
The Ustyurt Plateau

**Fig. 9.** Dynamics of annual DI residuals for different vegetation types in different regions.

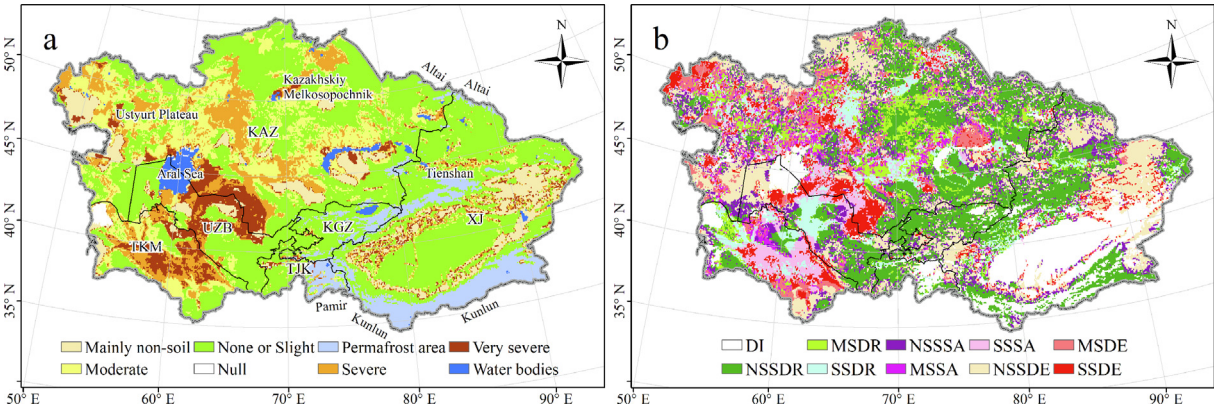


**Fig. 10.** Spatial distributions of soil salinity (a) and the superimposition of different degrees of soil salinization and desertification (b). KAZ: Kazakhstan; UZB: Uzbekistan; KGZ: Kyrgyzstan; TJK: Tajikistan; TKM: Turkmenistan; XJ: Xinjiang Province. The legend for (b): DA: sand sheets; NSS: no or slight salinity; MS: moderate salinity; SS: severe salinity; SA: stable area; DE: desertification expansion; DA: desertification reversion. The data on soil salinity were acquired from the Harmonized World Soil Database provided by the Food and Agriculture Organization of the United Nations (Fischer et al., 2008).

sparse vegetation (Fig. 9). Therefore, any long-term warming would restrain the growth of sparse vegetation and cause desertification expansion. However, we found that desertification expansion in the central region of eastern Xinjiang Province was triggered by human activities (Fig. 7f). This finding could be explained by overgrazing and vegetation degradation in Balikun County (Han et al., 2014). Accordingly, desertification in eastern Xinjiang Province tended to worsen, and the harnessing mission remained arduous (Li et al., 2004).

The desertification expansion of sparse vegetation was vulnerable to human activities and was observed to be a result of gas and oil reserve exploitation in the Ustyurt Plateau of Kazakhstan. Kazakhstan has the most abundant oil and gas resources among the five states of Central Asia, most of which are in the Ustyurt Plateau. We found that gas and oil are heavily exploited, and many wells are spatially concentrated in this region. Karnieli et al. reported that vegetation removal related to the exploitation of gas and oil appeared around the wells of the Ustyurt Plateau (Karnieli et al., 2008). Heavy vehicles for gas and oil exploitation can easily damage sparse vegetation. This vegetation damage might explain the observed expansion of desertification caused by human activities for sparse vegetation in this area (Fig. 7f). This result is consistent with a significant increasing trend in DI residuals for sparse vegetation in the Ustyurt Plateau (Fig. 9).

Sparse vegetation in the middle part of the Kyzylkum Desert and the western part of the Karakum Desert was scattered, with severe soil salinization under desertification reversion. This desertification process in the sparse vegetation was mainly triggered by salinization feedback. In this case, the interaction between hydrological processes and vegetation dynamics changes the balance of soil salinity, which also changes the conditions to be suitable for sparse vegetation growth. These phenomena can often occur in environments with shallow groundwater tables and sparse vegetation (Runyan and D'Odorico, 2010). Moreover, increased precipitation was found in these areas, and high positive correlations were observed between desertification reversion of sparse vegetation and precipitation in these areas (Fig. 7). Hence, these two factors can explain why areas with severe salinity and sparse vegetation were undergoing desertification reversion.

## 5. Conclusions

In Central Asia, the long-term desertification process was monitored from 1982 to 2012 using four indicators. By combining gridded temperature and precipitation data, statistical data of livestock number and crop area and gridded soil salinity data, we distinguished different driving factors of desertification for different vegetation types based on the correlation and residual analyses. The main results are summarized as follows:

(1) A significant desertification expansion was observed in the western part of Central Asia, whereas a significant desertification reversion was identified in the eastern part of Central Asia. Higher proportions of desertification expansion were distributed in areas with sparse vegetation and crops than in grasslands and forests. According to the change-year detection of desertification, a higher percentage of change-years from 1992 to 2002 was found in most vegetation types. The residual analysis revealed that precipitation and temperature were the major drivers of the desertification process in Central Asia, especially for grasslands, forests and sparse vegetation.

(2) The desertification process of different vegetation types and different regions resulted from different major driving factors. For grasslands and forests in the Altai and Tien Shan Mountains and southern Kazakhstan, increased precipitation was the main factor affecting desertification reversion. In contrast, grasslands of the Ustyurt Plateau, which showed a significant decreasing trend in precipitation, were under desertification expansion. For grasslands in eastern Kazakhstan, Tajikistan and Kyrgyzstan, pasture abandonment was a major driving factor affecting desertification reversion after the disintegration of the Soviet Union in 1991.

(3) The desertification of crops varied between the five Central Asian countries and Xinjiang Province. After the collapse of the Soviet Union, millions of hectares of croplands were abandoned in Kazakhstan, which exacerbated desertification expansion in croplands. In contrast, sparse vegetation was reclaimed as croplands in northern Xinjiang Province, which resulted in desertification reversion in this area. Moreover, because of excessive or inefficient irrigation water use, severe salt accumulation in croplands of the Amu Darya River delta occurred, resulting in desertification expansion in this region.

(4) For sparse vegetation in the Gurbantunggut and margins of the Taklimakan Desert in Xinjiang Province, increased temperature may be the main driving factor affecting desertification expansion. In eastern Xinjiang Province and the southern part of Turkmenistan, drought due to increased temperature and decreased precipitation is the major driver affecting the desertification expansion of sparse vegetation in these regions. In addition to climate change, the desertification expansion of sparse vegetation due to the exploitation of the gas and oil reserves in the Ustyurt Plateau of Kazakhstan was observed.

This study investigated the long-term desertification process and assessed the relative roles of its drivers for different vegetation types in Central Asia. Desertification is a very complicated process and is a consequence of multiple drivers. We identified the relative importance

of these driving factors of desertification for different vegetation types. Due to the limited number of long-term-series datasets available, only four indicators were chosen in this study for monitoring the desertification process, and other effects on desertification were not considered. In future research, additional indicators combined with a deep understanding of the desertification process for Central Asia will be critical.

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## Author contributions

Guli·Jiapaer designed this study. Liangliang Jiang processed the data, analysed the results and wrote the manuscript. Anming Bao, Alishir Kurban, Hao Guo, Guoxiong Zheng, Philippe De Maeyer provided analysis tools and technical assistance. All authors contributed to the final version of the manuscript by proofreading and providing constructive ideas.

## Conflicts of interest

The authors declare no conflicts of interest.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.04.067.

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